RL Vision Preliminary Research in Object Detection

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1 IDEAS

The following ideas were recommended from ChatGPT (https://chat.openai.com/share/cbf2de8a-220d-4735-8404-1f11c51bdd78):

(1) **Active Object Detection:** RL can be used to guide the object detection process. An RL agent can select regions of interest within an image for the object detector to focus on. By directing attention to the most relevant parts of an image, RL can improve the efficiency and accuracy of object detection.
(2) **Adaptive Hyperparameters:** Object detection models often have hyperparameters that need to be tuned for different scenarios. RL can be used to adaptively tune these hyperparameters based on the current environmental conditions. For example, the RL agent can learn to adjust the detection threshold or anchor box sizes to suit specific situations.
(3) **Reinforcement Learning for Object Tracking:** Once objects are detected, RL can be applied for object tracking. The RL agent can learn to follow and predict the movements of detected objects, which is especially useful in scenarios like autonomous vehicles or surveillance.
(4) **Continuous Learning:** RL can facilitate continuous learning for object detection systems. The model can be updated and fine-tuned in real-time as new data becomes available, adapting to changes in the environment or object appearances.

2 DEEP REINFORCEMENT LEARNING IN COMPUTER VISION: A COMPREHENSIVE SURVEY

The text provides a comprehensive overview of deep reinforcement learning (DRL) approaches for object detection.

- Object detection is a core problem in CV. DRL offers an alternative to deep learning methods like R-CNN, SSD, YOLO.
- DRL formulates object detection as an MDP. The agent takes actions to refine a bounding box to better match ground truth.
- Different DRL algorithms like DQN, policy gradient have been used. State representation includes image features and action history. Reward is typically IOU improvement.
- DRL has achieved strong results on datasets like PASCAL VOC, showing competitiveness with deep learning methods.

Some examples:

- Caicedo et al. (2015) used DQN with 8 bounding box actions. Achieved higher mAP than methods like MultiBox on VOC 2007.
- Jie et al. (2016) proposed a tree-structured DRL agent for hierarchical object detection. Improved on Fast R-CNN mAP on VOC 2007.
- Zhang et al. (2020) used DRL for efficient object detection in large images, with coarse and fine search. Outperformed methods like YOLOv3 on Caltech Pedestrian dataset.
- Chen et al. (2020) applied DRL for monocular 3D object detection from 2D images. Surpassed other methods like PointRCNN on KITTI dataset.
- Overall, DRL provides a complementary approach to deep learning for object detection with promising results on major datasets and tasks.

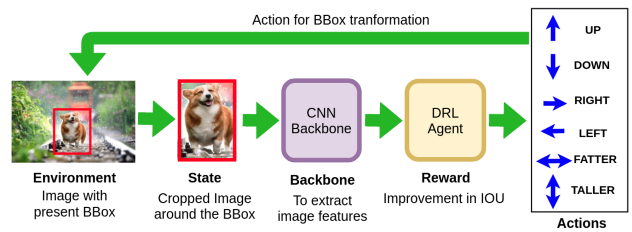

Figure 1: DRL implementation for object detection. The red box corresponds to the initial bounding box which for t=0 is predicted by some other algorithm or the transformed bounding box by previous iterations of DRL using the actions to maximize the improvement in IOU. Taken from [1].

[1]

3 OBJECT DETECTION WITH DEEP REINFORCEMENT LEARNING

The following key points summarise the novel deep reinforcement learning approach for object detection presented in this paper:

- Formulates object detection as a Markov decision process (MDP) and uses deep reinforcement learning to actively locate objects.
- Implements and compares two DRL methods:
  - Hierarchical method - agent chooses one of 5 subregions of image at each timestep.
  - Dynamic method - agent transforms bounding box with actions like translate, scale, deform at each step.
- State representation includes image features of current region and action history. Reward based on improvement in IOU. The Recall metric was also tested as a reward function in one of the conducted experiments.
- Uses DQN with experience replay to estimate Q-values. VGG16 used for image features.

- Tested on PASCAL VOC 2012 dataset. Performs ablation studies and hyperparameter tuning.
- Hierarchical method faster but can get stuck due to predefined regions. Dynamic method slower but bounding box can move freely.
- Achieves average IOU of 0.42-0.46 on some classes with tuned hierarchical model, 0.2-0.4 with dynamic model.
- DRL provides a new paradigm compared to standard deep learning for object detection. Has potential but current accuracy lags state-of-the-art.
- Limitations include class-specific training, struggles with multiple objects.
- Overall, presents a novel DRL approach for object detection and provides interesting analysis and results on PASCAL VOC. Further improvements in accuracy as well as multiple object detection via RL are required.
- https://github.com/ManooshSamiei/Object-Detection-Deep-Reinforcement-Learning

[2]

4 REINFORCEMENT LEARNING FOR VISUAL OBJECT DETECTION

The following key points summarises the deep reinforcement learning approach for object detection presented in this paper:

- Formulates object detection as a sequential decision process and solves it using reinforcement learning.
- At each time step agent takes a 'fixate' action to sample an image location or 'done' to terminate search and output detection.
- State consists of history of observed regions, selected evidence regions, fixations.
- Fixate action guided by evidence region to predict next location to attend using learned Gaussian policy.
- Done action outputs detected bounding box and confidence based on observed regions.
- Reward function balances detection accuracy and computational load.
- Learns policy to maximise expected long term reward using policy gradient method.
- Evaluated on PASCAL VOC 2012 detection dataset.
- Achieves 2 orders of magnitude speedup over sliding window detection with minor drop in AP.
- Analysis shows model adapts search length based on image, leverages context, and searches coarsely to finely.
- Limitations include reduced accuracy compared to state-of-the-art detectors.
- Provides a novel reinforcement learning formulation for object detection with promising results. Further gains in accuracy would improve applicability.

[3]

5 REINFORCENET: A REINFORCEMENT LEARNING EMBEDDED OBJECT DETECTION FRAMEWORK WITH REGION SELECTION NETWORK

The following key points summarises the deep reinforcement learning approach for object detection presented in this paper:

- Proposes ReinforceNet, a deep reinforcement learning framework for object detection.
- Formulates object detection as a Markov decision process.
- Agent iteratively transforms an initial bounding box by taking actions like translate, scale, aspect ratio change.
- Actions parameterised by a deep policy network based on VGG-16.
- State is features from ROI pooled CNN layers and a history vector.
- Reward is change in IOU after each action. Episode terminates when IOU > threshold.
- Trains policy network end-to-end using REINFORCE algorithm with a learned value function baseline.
- Evaluated on PASCAL VOC 2007 dataset.
- Achieves higher mAP than Fast R-CNN with same VGG-16 backbone. More efficient than R-CNN.
- Ablation studies analyse impact of state representations, reward definitions.
- Limitations include reduced accuracy compared to newer detectors like Faster R-CNN.
- Proposes a 'completeness' metric to evaluate how completely the agent explores the state space during training.
- Low completeness indicates agent converges prematurely without sufficient exploration.
- Identifies insufficient exploration as a key challenge in applying RL for object detection.
- Incomplete training leads to suboptimal policies that fail to generalize well.
- Implements curriculum learning strategy to increase completeness and improve exploration.
- Achieves higher completeness and mAP with curriculum training compared to standard training.
- Analyses the dynamics of completeness over training iterations to study agent's exploration behaviour.

[4]

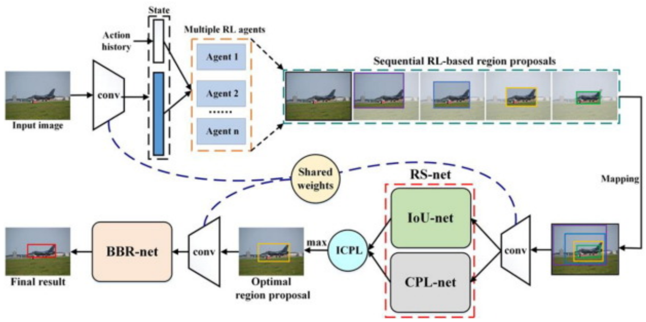

Figure 2: Technical pipeline of our proposed ReinforceNet. Firstly, input images are fed into CNN backbone to obtain feature maps. Secondly, RL agents execute a sequence of actions to locate the object by observing feature maps and simultaneously output a set of region proposals. Subsequently, RS-net including IoU-net and CPL-net is exploited to select the optimal region proposal. Finally, BBR-net is responsible for further refining the optimal one as the result. Taken from [4]

6 EXPLORING HOW WEAK SUPERVISION CAN ASSIST THE ANNOTATION OF COMPUTER VISION DATASETS

- The paper explores using class activation maps (CAMs) to assist with annotating computer vision datasets. CAMs can generate weakly supervised labels and localizations from image classifiers.
- They developed an interactive web application to emulate crowdsourcing image annotations for classification and localization tasks. This generated data to compare against the CAM models.
- Several CAM techniques were tested including Grad-CAM, Grad-CAM++, Score-CAM, and Faster Score-CAM. These were integrated with VGG16, MobileNetV2, and EfficientNetB0 image classifiers.
- Evaluation metrics:
  - Localization error (LE) from ILSVRC - accounts for false positives and false negatives
  - Variants of LE that separately measure false positives (LE_fp) and false negatives (LE_fn)
- Results:
  - CAM models saved 17-36% annotation time compared to human crowdsourcing
  - MobileNetV2 + Faster Score-CAM achieved the best localization error of 49.2%, outperforming humans by 9.7%
  - CAM models were more "confident" in their predictions than humans
- A second survey evaluated human ability to determine machine vs human annotations. Humans tended to assume human annotations were correct. Accuracy on the test was only 36.7%.
- Overall the results indicate CAMs have potential to assist with more efficient and accurate image annotation compared to purely manual approaches. Integration of human verification could further improve the annotations.

[5]

To do: 1. Main objective/problem from object detection dataset to image classification dataset 2. start with COCO dataset 3. try to replicate Figure 1 or find code for it 4. read andrea abela paper

REFERENCES

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